Received: 23 November 2023 | Accepted: 27 May 2024

DOI: 10.1002/poi3.402

RESEARCH ARTICLE

Quantifying water effluent violations and enforcement impacts using causal AI

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Funding information

Deloitte

Abstract

In the landscape of environmental governance, controlling water pollution through the regulation of point sources is vital as it preserves ecosystems, protects human health, ensures legal compliance, and fulfills global environmental responsibilities. Under the Clean Water Act, the integrated compliance information system monitors the compliance and enforcement status of facilities regulated by the National Pollutant Discharge Elimination System (NPDES) permit program. This study assesses temporal and geographic trends for effluent violations within the United States and introduces a novel metric for quantifying violation trends at the facility level. Furthermore, we utilize a linear parametric approach for Conditional Average Treatment Effect (CATE) causal analysis to quantify the heterogeneous effects of EPA and state enforcement actions on effluent violation trends at facilities with NPDES permits. Our research reveals insights into national pollutant discharge trends, regional clustering of all pollutant violation types in Ohio (G_i^* *Z*-score of 2.15), and priority pollutants in West Virginia (G_i^* *Z*-score of 3.07). The trend metric identifies regulated facilities that struggle with severe and recurring violations. The causal model highlights variations in state compliance and enforcement effectiveness, underscoring the successful moderation of violation trends by states such as Montana and Maryland, among others.

KEYWORDS
causal AI, effluent violations, hot-spot analysis, wastewater management, water policy

INTRODUCTION

Environmental governance in the United States stands on vigilant regulatory compliance monitoring, particularly within the National Pollutant Discharge Elimination System (NPDES). This system, established under the U.S. Clean Water Act (CWA) (Copeland, 1999), requires facilities to report pollutant levels through discharge monitoring reports (DMRs) as part of their NPDES permit obligations. Effluent violations, crucial to this oversight, occur when reported values in DMRs exceed established limits or fall below required minimum levels. These violations serve as vital indicators of facilities' noncompliance with CWA standards, which safeguard the nation's water bodies from pollution and preserve their integrity. The focus of this paper on the United States context is essential due to the unique regulatory and environmental challenges faced by the country in managing water pollution.

Effective December 21, 2016, all discharge monitor reports and forms designated by the Director for monitoring sludge use or disposal practices (The Code of Federal Regulations, 2023d) must be submitted electronically by the permittees. This mandate confronts several challenges related to the digital divide, including varying access to the necessary technology and the internet, the learning curve associated with digital platforms, ensuring system readiness and compatibility, and maintaining data security and privacy. The digital divide can be defined as the "gap between those who have and do not have access to computers and the internet" (van Dijk, 2006), which further can be extended as a group that has access to high computational power, fast internet, availability of the data, and relevant training, etc. compared to another group (Noll et al., 2001). A survey conducted by the California Association of Mutual Water Companies with more than 300 water systems uncovered that more than 40% of small water systems are not using any technology for monitoring daily operations (Ortega, 2021).

Further, the rapid development of technology, especially AI, creates a need for various skills and knowledge. This advancement can be termed a fourth revolution, and AI is already used in applications such as soft computing, water quality monitoring, and decision-support systems (Tiyasha et al., 2020). Recently, Rapp et al. (2023) surveyed 49 large drinking water utilities in 21 different U.S. states to uncover the use of AI in them. The results revealed that 69% (34/49) of water utilities have yet to use AI in the past or at the time of the survey for water systems' operations. This significant disparity in adopting AI technologies among water utilities highlights a critical aspect of the knowledge divide. Recently, the U.S. EPA has proposed a budget of $10,994 billion, out of which 9.2%, that is, $1,010 million, is dedicated to science and technology development (United States Environmental Protection Agency, 2024). This budget also details $1,239,895 thousand for statewide infrastructure assistance funds, which may help equalize access to technology, learning, and training to bridge the digital and knowledge divide.

A gap in technique and training hampers the conversion of information into knowledge, primarily due to the digital and knowledge divide. Addressing this gap requires defining policies and providing equitable access to technology, learning, and training (Opola et al., 2023). Moreover, the ethical, social, and legal perspectives are intricately connected within the water sector. Ethically, the issue revolves around water pollutants, which are closely linked to CWA regulations on industrial and municipal pollutant discharges affecting water quality, thereby touching on the social concern of water pollution (Copeland, 1999). Legally, this domain also includes open data policies, promoting the free and easy availability of water data (Zuiderwijk & Janssen, 2014), which enhances sustainability, management, and decision-making, aiding in policy development. Considering these aspects, this paper assesses the effluent violations at the facility level, which directly or indirectly contributes to ethical, social, and legal perspectives regarding state compliance and enforcement effectiveness.

Theoretical foundation and motivation

Environmental monitoring and enforcement operate within a decentralized framework in the United States, with the U.S. Code of Federal Regulations and the EPA setting the overarching regulatory standards. However, a substantial portion of permitting, inspection, and sanctioning responsibilities is delegated to state-level agencies. Understanding the dynamics between effluent violations and the spectrum of enforcement actions enacted by the EPA or state authorities is essential. The enforcement landscape, executed by the EPA or state entities, spans a series of actions ranging from administrative formal and informal actions to judicial proceedings (The Code of Federal Regulations, 2023a). In shaping the enforcement responses, the EPA or states employ a discerning approach, considering the type and severity of violations, evaluating their potential environmental and public health risks, and assessing the facility's capabilities to address these violations (United States Environmental Protection Agency, 2023e). As shown in Figure 1, the EPA's Office of Compliance maintains the integrated compliance information system (ICIS) for NPDES (ICIS-NPDES), a repository with robust data on permit compliance and enforcement status. This database allows for a detailed exploration of the causal relationships between effluent violations and enforcement strategies.

In the realm of environmental economics and policy analysis, as exemplified by the work of Gray and Shimshack (2011) causal inference techniques are employed to evaluate the efficacy of regulatory interventions on environmental quality. These researchers highlight the importance of identifying not just the presence of a statistical association between regulatory actions and environmental outcomes but the direction and magnitude of causation. Causation refers to how a change in a treatment variable results in a change of the outcome variable, which can be inferred from observational data with the use of causal graphical models (Anderson & Geras, 2022; Pearl & Mackenzie, 2018; Rohrer, 2018). More on this is in the causal methods section.

This research undertakes a comprehensive analysis of the trend in effluent violations. Leveraging advanced data-intensive techniques, such as spatial hot-spot analysis and

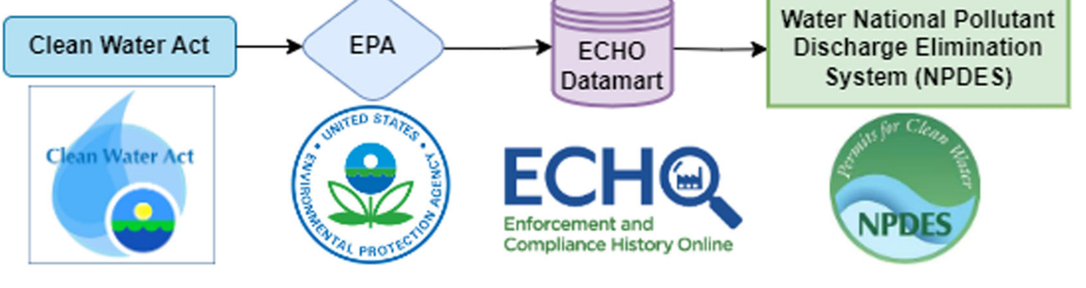

FIGURE 1 Clean Water Act data flow.

causal learning, we seek to elucidate the heterogeneous causal effects from enforcement actions initiated by federal and state governments at the facility level.

Background: Violations and enforcements

NPDES is a permit program authorized to state governments by the EPA that addresses water pollution in the United States (United States Environmental Protection Agency, 2023b). Under the NPDES, the EPA includes eight programs: (1) Animal feeding operations, (2) Aquaculture, (3) Industrial wastewater, (4) Municipal wastewater, (5) National pretreatment program, (6) Pesticide permitting, (7) Stormwater, and (8) Vessel discharges. The EPA holds enforcement authorities to address violations in private and federal facilities. These violations are discovered based on the regular reporting required by environmental regulations, EPA or state inspections, data monitoring, and notifications provided by the facilities (United States Environmental Protection Agency, 2023e). In 2022, the EPA reported that there are about 46,000 NPDES-permitted facilities, out of which 9% (≈ 4,140) were in significant noncompliance (SNC) (United States Environmental Protection Agency, 2022). These SNCs vary, and causes include unauthorized discharge, overflow, exceeding effluent limits, and failure to submit reports. Some of them could cause pollution affecting aquatic functioning and ecosystems (Smolders et al., 2004). Ajadi et al. (2016) noted that the exceeded value of pH, iron, zinc, dissolved oxygen, and nitrate poses a health risk to people receiving this water for domestic use. Wastewater processing is also an important step in providing clean water for farming and agricultural use, ensuring safe and connected water and food supply chains (Sobien et al., 2023). For example, exceeded values of toxic metals in the water can affect the soil's chemical parameters and could affect the quality of the rice (Afrad et al., 2020; Ladwani Kiran et al., 2012). A study conducted by the United States Geological Survey revealed that wastewater processes can affect the discharge of nutrient loads, influencing effects on environmental and biological conditions (Graham et al., 2014). This way, the SNC can affect aquatic ecosystems, public health, agriculture, and environmental and biological conditions. Consequently, it is indispensable for the EPA and States to implement policy-based enforcement actions.

The enforcement process defined by the EPA, as illustrated in Figure 2, includes informal and formal actions. In informal enforcement, the EPA issues warning letters or notices of violations (NOVs) to facilities. Formal enforcement actions by the EPA include issuing a notice of noncompliance, negotiating Federal Facilities Compliance Agreements, and pursuing judicial actions under the CWA. Similarly, U.S. states are responsible for enforcement actions at facilities. For informal actions, states typically issue warning letters,

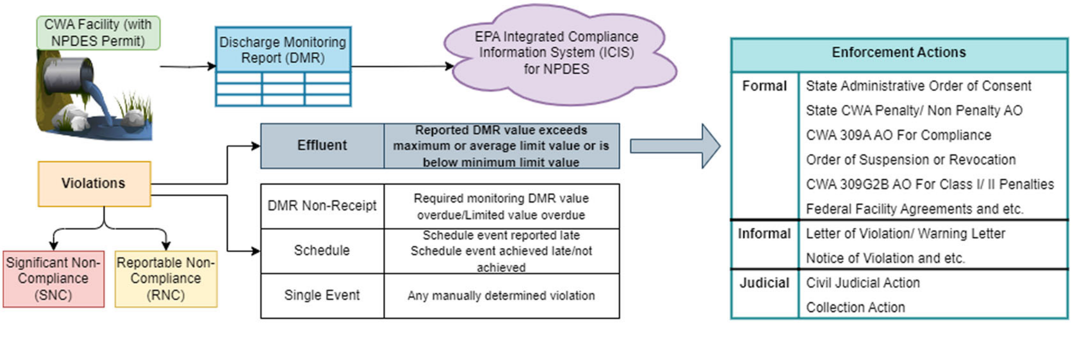

FIGURE 2 Effluent violation types and enforcement process for federal facilities.

NOVs, or show cause letters, which are informal warnings stating the intent to pursue enforcement but aiming for a mutual agreement. Formal actions taken by states can involve penalty orders, suspension or revocation orders, emergency orders signed by the governor, and administrative orders.

The EPA's approach to enforcement includes a range of compliance assurance tools, such as compliance assistance, self-audits, and both informal and formal enforcement actions, as part of its national compliance initiatives. These initiatives aim to improve compliance with environmental laws and enhance shared accountability between the EPA, states, and federally recognized Indian tribes with authorized environmental programs (United States Environmental Protection Agency, 2023d). Formal enforcement remains crucial for addressing serious noncompliance and creating general deterrence, indicating the agency's commitment to stringent compliance enforcement.

These enforcement mechanisms are essential in understanding the heterogeneous effects of EPA's actions on effluent violation trends. The blend of informal warnings and formal judicial actions reflects the EPA's strategy to encourage compliance while reserving the right to impose stricter penalties for serious or repeated violations.

Related work

In this study, we use hot-spot analyses and causal learning to study the heterogeneous effects of the EPA and state regulator enforcement actions. Hot-spot analysis is an approach of identifying spatial patterns in data, particularly in regions where the local structure of these patterns is unusual compared to its surrounding (Ord & Getis, 1995). As noted by Barthel et al. (2015) the hot-spot analysis has provisions to include technical and non-technical information that is needed for decision-making in government, business, and civil society. There are four main steps in conducting hot-spot analysis: (1) Goal and scope definition, (2) Data gathering, (3) Hot-spot identification and validation, and (4) Prioritizing action (Barthel et al., 2014). We focus on the first three steps, with the goal of understanding which states and regions in the United States are more prone to violations and quantifying spatial and temporal trends. We gather data provided by the EPA effluent discharge violations, analyze for hot- and cold spots using the Getis–Ord G_i^* statistic (Ord & Getis, 1995), and analyze temporal trends of violations with a set of per facility metrics. Recent applications of hot-spot analysis in the water domain include: analysis of water insecurity (Cooper-Vince et al., 2018), water footprints and groundwater decline (Multsch et al., 2016), water main failures (García et al., 2018), water quality inequality (Neville et al., 2022), and Safe Drinking Water Act (SDWA) violations (Allaire et al., 2018).

The causal analysis is a study of understanding how actions, interventions, or treatments can affect the outcome of interest (Bojinov et al., 2020). Causal analysis can help make effective policy and management recommendations on climate, epidemiology, financial regulation, trade, pollution, and other sectors (Sugihara et al., 2012; Wang et al., 2022). The essence of causal AI lies in its ability to transcend beyond correlations and predictions. It enables policymakers to identify effective strategies and make informed decisions based on a deeper understanding of the underlying causal mechanisms. In water resource management, causal analysis has been used for different applications, such as the investigation of water quality (Zavareh et al., 2021), river salinity and the Ganges water agreement (Penny et al., 2020), anomaly detection in water treatment (Koutroulis et al., 2022), and understanding complex ecosystems (Sugihara et al., 2012).

Research question

The main objective of this study is to analyze the trend of NPDES effluent violation and the causal effects of enforcement actions. The regulatory actions from EPA and state regulators are used for the analysis. To achieve the objective, the following research questions are investigated within the scope of this paper:

1. What are the temporal and geographic trends in effluent violations within the U.S.? With a specific focus on identifying geographic hot-spots for the most concerning and high-priority pollutants.
2. How are facilities' effluent discharge trends quantified to assess severe and recurring violations?
3. What are the heterogeneous causal effects of enforcement actions undertaken by the EPA and individual U.S. states?

This paper is structured as follows: Second section describes the materials and methods used for this study. These details include background on data, hot-spot analysis, effluent trend metric assessment, and casual model. Next, third section reports the results from temporal and spatial trend analysis. This section also includes results from hot-spot analysis and causal model. Furthermore, fourth section discusses the result and their implications for policy improvement.

MATERIALS AND METHODS

Data

The data for this study sources from the Enforcement and Compliance History Online (ECHO), a comprehensive repository that provides integrated access to regulatory and compliance information for over 800,000 regulated facilities. ECHO encompasses data related to critical environmental statutes, including the Clean Air Act, CWA, Resource Conservation and Recovery Act, SDWA, and Toxics Release Inventory (TRI) (United States Environmental Protection Agency, 2023a).

Specifically, this study utilizes the NPDES data obtained through the ECHO exporter. The core dataset extracted from ECHO includes violation data, encompassing system-generated records. It is noteworthy that the ICIS automatically generates three primary types of violations, namely schedule violations, effluent violations, and DMR nonreceipt violations, as shown in Figure 2. By narrowing the scope of the analysis, we filter down to only consider effluent violations between years 2008 and 2022 within the United States.

To gain a comprehensive understanding of the trends in effluent violations and their associated enforcement actions, we integrate the effluent violation data with three additional datasets—these datasets contain information regarding whether enforcement actions were triggered to respond to the identified violations. We create a holistic and informative dataset by combining these datasets through a systematic data integration process. This integrated dataset allows us to track the trends in violations over time. It also provides insights into which specific violations at each facility triggered enforcement actions, the nature of the actions taken, the responsible regulatory agencies, and other relevant details. This enriched dataset serves as the foundation for our hot-spot analysis, empowering us to explore the causal impact of enforcement actions on pollutant violation trends while accounting for state-level variations.

Hot-spot analysis

For the hot-spot analysis, we use the Getis–Ord G_i^* to measure the local statistic of clustering (Getis & Ord, 1992; Ord & Getis, 1995). Getis and Ord (1992) referred to this clustering as a concentration of weighted points (in our case, violations) within a radius of distance d around an origin. Other researchers in the water and groundwater quality field have used the Getis–Ord statistic for hot-spot analysis of drinking water violations in the United States (Allaire et al., 2018), of poor ambient water quality from metal contamination, (Neville et al., 2022) of groundwater quality in an aquifer (Mohamadi et al., 2023), and water quality of the South Platte Watershed (Schliemann et al., 2021). The statistic measures whether some focal state i stands out from the surrounding states j given the sum of violations in those states compared to the total number of violations in the country. Specifically, it calculates a degree of association using weights for surrounding states within some distance d (Getis & Ord, 1992). We use the queen contiguity (Suryowati et al., 2018) with equal weight between the focal state w_i and adjacent states w_j, such that the sum of all w is 1 amongst a state and all its neighbors. The Getis–Ord statistic and spatial weights are calculated using the exploratory spatial data analysis (ESDA) library in the Python Spatial Analysis Library (PySAL) package (Rey & Anselin, 2007). The formula for the Getis-Ord statistic can be expressed as (Allaire et al., 2018; Ord & Getis, 1995):

$$G_i^*(d) = \frac{\sum_{j=1}^{n} w_{i,j}(d)x_j - W_i\bar{x}}{s\sqrt{\frac{n\sum_{j=1}^{n} w_{i,j}^2 - W_i^2}{n-1}}}, \tag{1}$$

where x_j is number of violations in state j, $\bar{x}$ is the mean of x_j, s is the standard deviation of x_j, $w_{i,j}$ is the spatial weight between states i and j, W_i is sum of weights $w_{i,j}$, and d is the threshold distance (Allaire et al., 2018). We plot Z-scores of the calculated statistic, which is the difference between $G_i^*(d)$ and the expected value (or mean G_i) normalized by the standard deviation. The Z-score shows how many standard deviations the G_i^* statistic is above (hot-spot) or below (cold-spot) the *global* average of the U.S. states.

Effluent trend metric assessment

In this study, the assessment of the "violation trend" for each facility is meticulously formulated through a comprehensive set of metrics:

- Violation frequency: This metric involves counting unique effluent violations, providing an essential baseline for understanding the frequency of regulatory breaches. It offers a quantifiable measure of how often a facility fails to comply with regulatory standards.
- Violation severity score: Violation severity score is calculated as the percentage of SNC violations relative to all recorded violations. The categorization of pollutants as SNC is determined using the quarterly noncompliance report pollutant code (United States Environmental Protection Agency, 2023c), as designated by the EPA. It represents the seriousness of the violations, distinguishing between routine and more severe incidents.
- Temporal trend: Temporal patterns are estimated using the Mann–Kendall test to capture evolving compliance trends over time. This method examines whether the compliance behavior of a facility is improving and can also state the degree of improvement.
- Recurrence interval: The recurrence interval metric calculates the average time-span between violations to represent the regularity of noncompliance incidents. This measure

helps in understanding the consistency of violations, indicating whether they are isolated events or part of a recurring pattern of noncompliance.

- Duration and magnitude of violations: The number of months covered by the DMR for which the effluent violation occurs. This metric assesses the duration of violations, which is crucial for evaluating the long-term environmental impact.

The Mann–Kendall trend test (Hussain & Mahmud, 2019) is a nonparametric test used to evaluate whether the time series have an increase or decrease trend over time. The test analyzes the sign of the difference between later-measured data and earlier-measured data, $(y_j - y_i)$, where $j > i$, and assigns the integer value of 1, 0, or –1 to positive differences, no differences, and negative differences, respectively. The test statistic, S, is then computed as the sum of the integers:

$$S = \sum_{i=1}^{n-1} \sum_{j=i+1}^{n} \text{sign}(y_j - y_i), \tag{2}$$

where $\text{sign}(y_j - y_i)$, is equal to +1, 0, or –1 as indicated above.

When S is a large positive number, later-measured values tend to be larger than earlier values, indicating an upward trend. When S is a large negative number, later values tend to be smaller than earlier values, indicating a downward trend. No trend is indicated when the absolute value of S is small. The test statistic τ can be computed as:

$$\tau = \frac{S}{n(n-1)/2}, \tag{3}$$

which has a range of –1 to +1 and is analogous to the correlation coefficient in regression analysis. The null hypothesis of no trend is rejected when S and τ are significantly different from zero.

Finally, we use a python package StandardScaler (Pedregosa et al., 2011) to scale five metrics outcomes to unit variance and sum them up to generate one trend score for each facility. By integrating these multidimensional metrics, our approach ensures a robust evaluation of the "violation trend," enriching our insights into the compliance status of individual facilities.

Causal learning for water policy

The relationship between correlation and causation can be stated as "Correlation implies association, but not causation. Conversely, causation implies association, but not correlation" (Altman & Krzywinski, 2015). Causation and correlation are two separate and distinct statistical terms that are not interchangeable, but are linked via associations in the data (Anderson & Geras, 2022). Meaning results from the hot-spot analysis, any correlations in the maps, cannot be used for claims of causation. Any associations that do appear, however, can be the start of further analysis by using separate causal analysis methods. Causation is difficult to prove, but can be inferred from observational data by using causal graphical models to understand and control for confounding variables. Observational data is useful for situations where randomized controlled trials are unethical or impractical (e.g., trying to force state regulatory agencies to adopt certain effluent violation policies) (Pearl & Mackenzie, 2018). From a causal graph, we can understand the causal links and their direction between variables and know which variables to control to prevent backdoor connections, and once done we can estimate the causal effect between a particular treatment and outcome, but this is all predicated on the assumption that the causal graph correctly captures the true causal links (Rohrer, 2018).

In this study, our causal model and graph are constructed at the individual facility level, where each unique facility record serves as the foundation for our analysis. Utilizing advanced effect estimators from EconML (Battocchi et al., 2019) and the DoWhy framework for identification criteria and controlling the causal graph for the backdoor criteria (Sharma & Kiciman, 2020), our causal inference model incorporates key parameters. The treatment variable in our model is defined as the percentage of violations that triggered enforcement actions by the EPA and individual U.S. states. We introduce the state as a critical factor in addressing the inherent heterogeneity across facilities. Since there are substantial variations in the percentage of violations leading to enforcement actions observed across different states, we study the heterogeneous enforcement percentage for permitted facilities within their exclusively associated state. This approach allows us to capture the diverse enforcement behaviors observed at the state level.

Furthermore, we incorporate 15 specific pollutant indicators: (1) nitrogen, (2) phosphorus, (3) organic enrichment, (4) solids, (5) pathogen, (6) metals, (7) CWA priority pollutants, (8) Compensation and Liability Act (CERCLA) hazardous substance, (9) TRI chemicals, (10) temperature, (11) Gen Radioactivity, (12) radionuclides, (13) color, (14) whole effluent toxicity, and (15) polyfluoroalkyl substances (PF). For each facility, we create flags to determine whether the top three pollutants within the facility are nitrogen, phosphorus, metals, or other toxic chemicals. These pollutant indicators served as confounding variables, enabling us to control for potential confounding factors associated with violation types and enforcements. This model architecture, as shown in Figure 3, ensures a robust causal estimate between enforcement actions and effluent violations within the unique context of each facility. We estimate causal effects using linear parametric conditional average treatment effect (CATE) models as below:

$$
\begin{gathered}
Y = \theta(X) \cdot T + g(X, W) + \epsilon, \\
T = f(X, W) + \eta, \\
\text{s.t. } E[\epsilon | X, W] = 0, E[\eta | X, W] = 0,
\end{gathered}
\tag{4}
$$

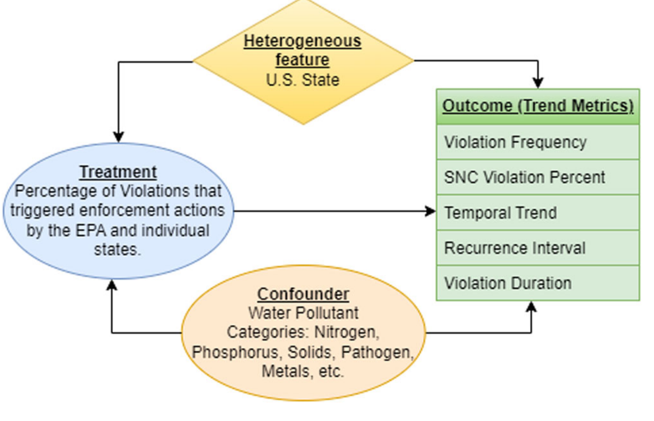

FIGURE 3 Causal graph.

where Y is the trend score from the five metrics, T is the treatment represented by the percentage of violations that triggered enforcement actions by regulatory agencies. The fifteen pollutant confounders are represented by W, which could potentially affect T and Y at the same time. We use one-hot encoding on the state name to create the fixed effect heterogeneous feature X. Now, we re-write the equations to estimate the constant marginal CATE $\theta(X)$.

$$Y - E[Y|X, W] = \theta(X)\cdot(T - E[T|X, W]) + \epsilon. \tag{5}$$

The estimated causal effect is calculated in three stages. First, we predict the outcome and treatment from the controls (confounders and heterogeneous features), respectively. Then, we calculate the residuals as follows:

$$\begin{cases} g(X, W) = E[Y|X, W] \Rightarrow \tilde{Y} = Y - g(X, W) \\ f(X, W) = E[Y|X, W] \Rightarrow \tilde{T} = T - f(X, W) \end{cases}. \tag{6}$$

Finally, we solve the regression on the residual and minimize a regularized empirical square loss of the form.

$$\begin{cases} \tilde{Y} = \theta(X)^{*}\tilde{T} + \epsilon \\ \theta(X) = <\vec{a},\ \phi(X)> \end{cases},$$

$$\text{i. e. },\ \hat{\Theta} = \arg\min_{\Theta} E_n[(\tilde{Y} - \Theta^{*}\tilde{T} \otimes \phi(X))^2] + \lambda R(\Theta), \tag{7}$$

where $R(\Theta)$ is L1 regularization here in the final model because we chose SparseLinearDML as our best candidate. Specifically, it employs an implementation of the Debiased Lasso algorithm (Bühlmann & Van De Geer, 2011), which corrects the inherent bias of the Lasso estimator by leveraging its asymptotic normality properties.

As a result, we obtain a coefficient table that portrays the $coef_{ij}$ parameter vector for each outcome i and treatment j. For every outcome i and treatment j the CATE $\Theta_{ij}(X)$ has the form:

$$\Theta_{ij}(X) = X'\text{coef}_{ij} + \text{cate\_intercept}_{ij}. \tag{8}$$

Overall, the double machine learning framework combines machine learning predictions with econometric techniques to estimate treatment effects while accounting for high-dimensional confounders (pollution categories). The estimated causal effect represents how the trend score changes on average with a unit change in the enforcement percentage, holding other covariates constant.

RESULTS

Temporal trends for effluent violations

The DMR data analysis reveals temporal trends in effluent violations. As shown in Figure 4, the dataset spans from 1983 till now, providing insights into long-term compliance patterns. Between 1983 and 2008, there was a substantial increase in violations, rising from 15 in 1983 to a peak of 134,765 in 2008, reflecting a significant growth in data availability and

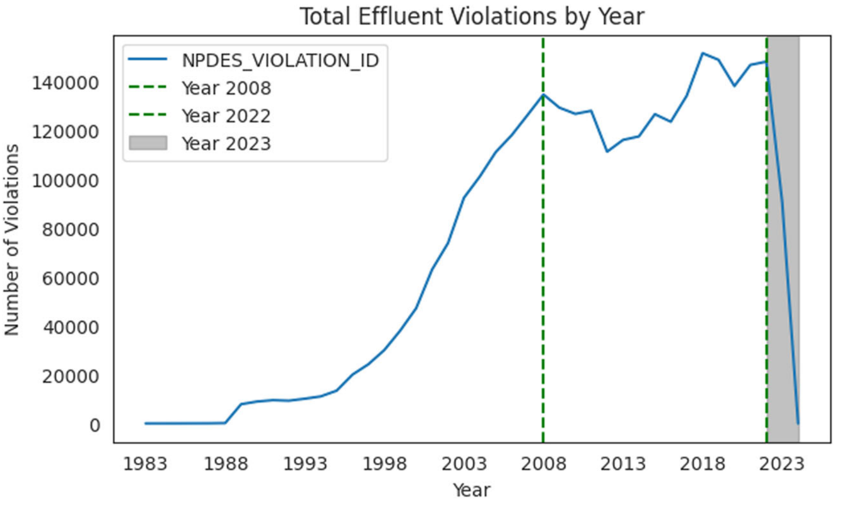

FIGURE 4 Total effluent violations by year.

compliance challenges during this period. Subsequently, from 2008 to 2013, there was a modest decrease, with violation counts dropping to 116,157 in 2013. However, the trend reversed in the following years, with violation counts steadily increasing to 148,232 by 2022. Due to incomplete data in the NPDES database, we opt to concentrate our analysis on effluent violations occurring after the year 2008 for hot-spot analysis and causal modeling.

Between 2008 and 2022, a total of 10,855 NPDES-permitted facilities had at least one effluent violation, and this number exhibited a growing trend in tandem with the violation counts. During this period, there were a total of 1,898,029 violations reported, with 410,563 (21.6%) of them triggering enforcement actions. Notably, a single violation can result in multiple enforcement actions, both informal and formal. As a result, the majority of enforcement actions were administrative formal actions (290,633), with 186,488 categorized as administrative informal, and 9,053 classified as j-udicial actions.

As depicted in Figure 5, the predominant pollutant categories observed in effluent violations include Nitrogen, often referred to as "Ammonia," and Solids, commonly denoted as "Solids, total suspended." In addition, there is a rapid increase in violations related to pathogens. Pathogens, defined as organisms causing diseases in their hosts, include frequently violated pollutants such as "fecal coliforms" and "*Escherichia coli*, *Enterococci*" (United States Environmental Protection Agency, 1999a). Metal related violations have exhibited a substantial increase since 2014, while phosphorus is a prevalent pollutant type in violations, characterized by a relatively stable trend over time.

Spatial trends of violations and enforcement actions

Hot-spot analysis shows regions and U.S. states with a greater than average (hot-spot) or a less than average (cold-spot) number of violations or enforcement actions. Figure 6 compares the G_i^* statistic for all violations of the NPDES effluent regulations (map on the left) to the percentage of those violations that trigger an enforcement action from the EPA or state regulator (map on the right). The Z-score normalizes results, so labels on the map are the number of standard deviations of the G_i^* statistic above or below a specific state from the

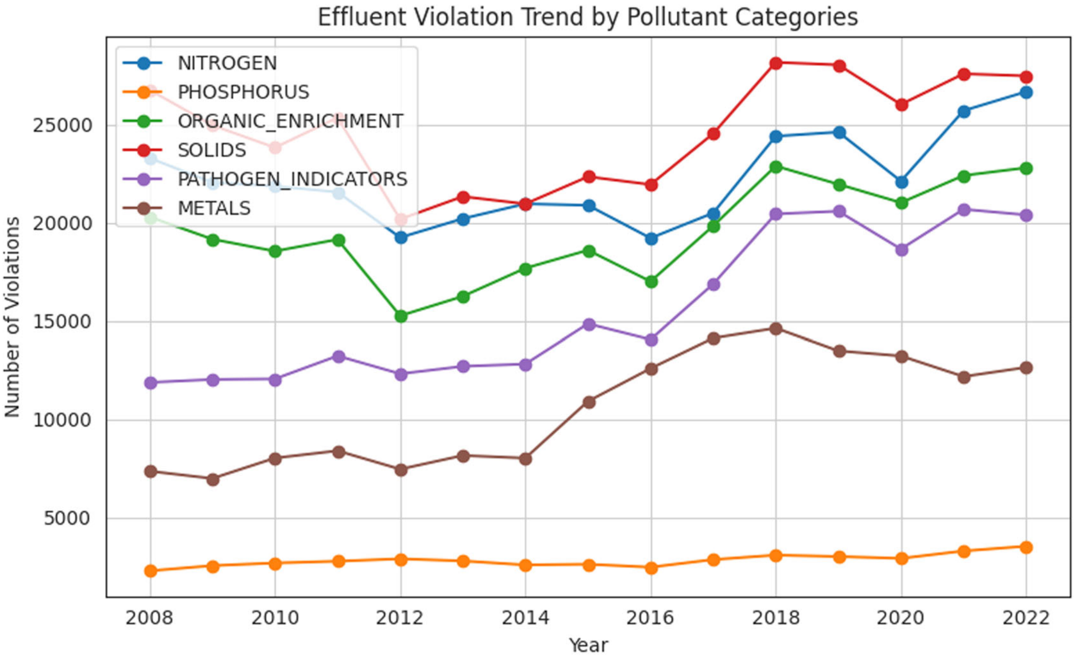

FIGURE 5 Effluent violation trend by pollutant categories.

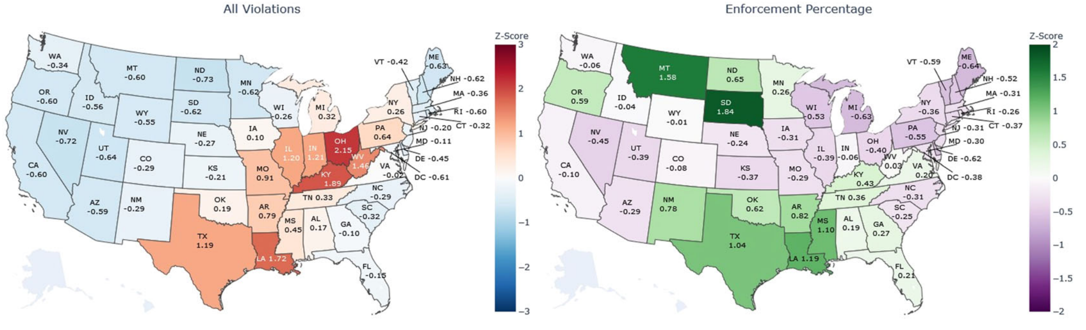

FIGURE 6 Local Getis–Ord G_i^* statistic hot-spot analysis for the number of all effluent violations compared to the percentage of enforcement actions in the ICIS-NPDES dataset. A positive Z-score indicates a greater number of violations (map on the left in red) or a greater percentage of violations that trigger an enforcement action (map on the right in green) above the national mean.

national average. A high or low Z-score is only an indication that a region or state has more or less violations than the national average; it is a relative measure, not an absolute one.

In the left-hand map in Figure 6, we see Ohio has the greatest score (2.15) by a fair margin, with Kentucky (1.89), West Virginia (1.46), Indiana (1.21), and Illinois (1.20) trailing right behind in this Rust Belt and eastern North Central region (U.S. Census Bureau, n.d.) overlap. This region is also defined primarily by the Ohio watershed (U.S. Geological Survey, n.d.). We see another regional hot-spot with Louisiana (1.72) and Texas (1.19) in the western South Central region (U.S. Census Bureau, n.d.), or the Lower Mississippi and Texas-Gulf watersheds, respectively (U.S. Geological Survey, n.d.). What these hot-spots show is both a regional increase of NPDES effluent violations in the eastern North Central region and Ohio watershed, and a larger concentration in Ohio compared to its surrounding states in the region. There are no cold-spots as concentrated as the hot-spots listed, that is, there are no cold-spots of Z-score less than −1. Regions with the lowest scores include the West, northeastern Midwest, and Atlantic Coastal.

The map on the right-hand side of Figure 6 shows hot-spots for the percentage of violations that trigger enforcement actions. Here, a greater Z-score (green) means a greater number of enforcement actions are taken by the EPA or state regulators than is expected given the national average. We see South Dakota with the greatest score of (1.84) followed by its neighbor Montana (1.58) in this boundary between West and Midwest (U.S. Census Bureau, n.d.). Another area of high enforcement is the South Central region (U.S. Census Bureau, n.d.) with Louisiana (1.19), Mississippi (1.10), and Texas (1.04).

There are no cold-spots less than −1, but we see that the Northeast and eastern Midwest have the lowest G_i^* Z-score for enforcement percentage, meaning there is a low concentration of enforcement actions for these regions. Coupled with low violation G_i^* statistic Z-scores, this might not be as concerning. However, Ohio (−0.40) and Illinois (−0.39) have some of the highest G_i^* statistic Z-scores for violations and lower than average enforcement actions taken. Kentucky and West Virginia are also in the same region of higher violations in the Ohio watershed, but break the trend with greater than average enforcement percentage Z-scores of 0.43 and 0.03, respectively.

The takeaway for these maps is the increased concentration of NPDES effluent violations in the Ohio watershed, without a matched percentage of those violations triggering enforcement actions in Ohio, Indiana, and Illinois. This region, and particularly those states, warrants additional focus to see if there are explanations in the estimation of heterogeneous treatment effects in the causal analysis. There are states with elevated violations, like Texas and Louisiana, but despite this, they also have an elevated percentage of enforcement actions for those violations, meaning there could be actions or protocols in place to better deal with them or take action when they arise.

The enforcement percentage hot-spot map highlights states and regions with potentially good policies that drive better enforcement actions, like in Montana and South Dakota, or it could be a matter of fewer violations to begin with, so a greater percentage of enforcement is more achievable. Because most of the West has below average concentrations of violations than the rest of the country, it is more likely that the combination of lower numbers of violations and policies in place have resulted in Montana and South Dakota having higher enforcement percentages than the national average.

Violation hot-spots for nitrogen and CWA priority pollutants

We focus on nitrogen and the CWA priority pollutant lists in this study. Nitrogen (including nitrates, nitrites, and ammonia) is a common agricultural and municipal sewage runoff which can cause problems in water bodies through harmful algal blooms (Schmale et al., 2019) and has been studied extensively as a harmful pollutant in drinking water (Allaire et al., 2019, 2018; Levin et al., 2023; Pennino et al., 2017, 2020; Schaider et al., 2019). We used the nitrogen category of pollutants as defined in the EPA NPDES DMR parameter to pollutant category crosswalk table[1]. The CWA priority pollutants (The Code of Federal Regulations, 2023b) is a list of toxic chemicals that the EPA has developed testing methods for to make a more practical and enforceable version of the toxic pollutant list (The Code of Federal Regulations, 2023c)[2]. The priority pollutant list focuses more on harmful chemical compounds and metal elements, and does not include nitrogen, phosphorus, or pathogens. Given the seriousness of both nitrogen and the CWA priority pollutants (albeit in very different effects and modes of action) and that these categories are non-overlapping, we analyze them separately in this section.

For the nitrogen violation hot-spot analysis, shown in the left-hand side map in Figure 7. The greatest hotspot is in Ohio with a G_i^* Z-score of 2.75, followed by Kentucky (1.76), Indiana (1.66), Illinois (1.31), and West Virginia (1.14). This is the same Ohio watershed region that had elevated Z-scores for all violation types in Figure 6. Michigan has an elevated nitrogen violation *Z*-score, meaning it has a greater difference in nitrogen violations above the national average compared to all violations. On the other hand, we see Texas and Louisiana have much lower *Z*-scores than previously. The same colder spots in the West, northeastern Midwest, and Atlantic Coastal regions for all violations have lower *Z*-scores for nitrogen violations. Overall, we see a very similar pattern of nitrogen violation hot-spots across the country as we did with all violations.

The right-hand side map in Figure 7 shows the G_i^* *Z*-scores for the CWA priority pollutant list violations. There are fewer hot-spots overall for these types of violations. The greatest hot-spot is West Virginia with a *Z*-score of 3.07, followed by Ohio (1.29) and Kentucky (0.89). This hot-spot region is much smaller than we saw for nitrogen and all violations, and it has shifted east in the Ohio watershed centering on West Virginia. We also see some Atlantic coast states go from below average for all violations to above average for priority pollutants: Connecticut, Maryland, and Virginia; however, this shift is only a small change in *Z*-scores. Another noticeable shift in the *Z*-score is in Washington state. Colder regions include the northern Mountain, northwestern Midwest, and southern Atlantic coastal regions.

For both the nitrogen and priority pollutant (Figure 7) hot-spot analyses, we see the same significant hot-spot region as we did for all violations in Figure 6, that is the Ohio watershed region (U.S. Geological Survey, n.d.), which includes the states Ohio, West Virginia, Kentucky, Indiana, and Illinois. While the concentration of nitrogen violations closely matched the concentration of all violations, there was a shift in distribution for the CWA priority pollutant violations. West Virginia is a major hot-spot for the priority pollutant violations, and there is an overall shift from the Ohio watershed east to the Mid-Atlantic watershed. We also notice a slight increase in the concentration of priority pollutant violations in Washington state compared to nitrogen and all violations. The Getis–Ord statistics highlight hot-spots that stand out from the average, and while we cannot make absolute statements about the number of violations using this method, it does point us to regions and U.S. states that likely require more scrutiny of policy to understand why these regions are so much greater than the average. Also, the statistic does not indicate that a cold-spot is not below some threshold where violations are not a concern, only that it is

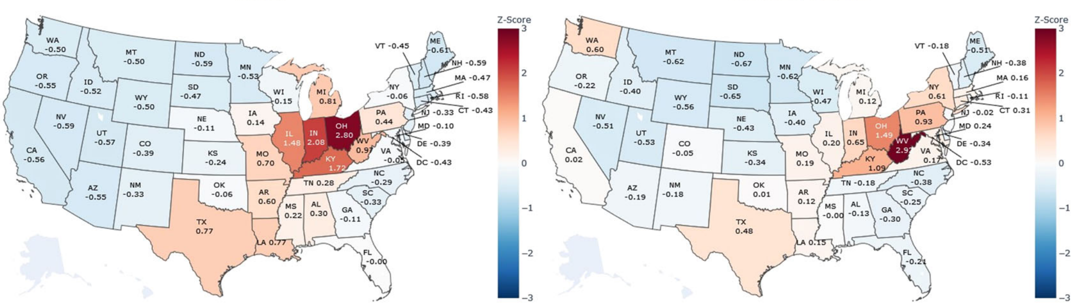

FIGURE 7 Local Getis–Ord G_i^* statistic hot-spot analysis for the number of nitrogen (left side) and CWA priority pollutant (right side) effluent violations in the ICIS-NPDES dataset. A positive *Z*-score (red) indicates a greater number of violations above the national average, while negative *Z*-scores (blue) indicate below average violations.

below the average. Cold-spots, however, can indicate regions and states where policy might be working better than others or regions where the selected pollutants are less prevalent to begin with.

Causal model results

We utilize the EconML library and DoWhy framework to study the heterogeneous effects of enforcement actions undertaken by the EPA and individual states on the effluent violation trends of NPDES permittees. After fitting a causal model, we obtain a causal effect size called estimate for heterogeneous factor state. To ensure the stability and generalizability of our results, we execute the causal model five times with different random seeds. We evaluate the statistical significance of each estimate obtained by examining the p-value and confidence interval. Estimates with a p-value less than 0.01 in all five runs are considered statistically significant and are listed in Table 1, along with their median estimate. In addition, we examine the contributions of each of the five metrics to the state-level causal estimation, enabling a more substantive discussion to interpret the dynamics of enforcement action influence and effluent trend characteristics.

Our analysis reveals distinct patterns in the causal effects across different states. In states with negative estimated causal effects, there is a discernible trend of improved wastewater treatment among facilities, with an increased likelihood of receiving regulatory actions in response to violations. Conversely, in states with positive estimated causal effects, the facilities' violation trends are not cooperating with enforcement activities. The root causes for such disparities may vary, from insufficient enforcement documentation to pervasive trends in effluent violations.

To elucidate the dynamics within specific states, we incorporate comprehensive statistics, including the total number of effluent violations, the count of violations with enforcement actions, the total of permitted facilities, and the number of actions undertaken by the EPA and State. As shown in Table 1, Wyoming and Michigan have the most negative estimates of −12.925 and −9.993, and both states exhibit a less than 2% enforcement percentage. One possible reason behind this might be incomplete enforcement records.

TABLE 1 State-level enforcement estimation results from causal AI.

State	Causal estimate	Enforcements	Total violations	Facilities	Enf %	EPA Enf	State Enf
IN	1.326	16,303	69,367	1,621	23.50%	318	18,842
MD	−3.563	4,001	26,372	842	15.17%	0	4,001
MT	−2.57	10,731	13,936	367	77.00%	315	13,408
OK	1.654	14,618	37,894	658	38.58%	13	14,959
TX	1.336	46,876	118,000	3,493	39.73%	8,890	50,420
WV	−1.583	26,163	121,596	2,297	21.52%	44	26,122
MA	2.504	3,522	22,790	452	15.45%	3,189	443
WY	−12.925	171	10,745	604	1.59%	0	171
MI	−9.993	23	17,598	813	0.13%	21	2
ID	−1.882	1,750	13,360	233	13.10%	1,860	8

Note: Only show States with a significant estimate (p-value smaller than 0.01).

Integrating violation data from different states, tribes, and territories with varying systems (direct use of ICIS-NPDES, hybrid use, and full batch systems) into a unified reporting framework may have influenced the consistency and reliability of NPDES compliance data (United States Environmental Protection Agency, 2007). Wyoming demonstrated a consistent pattern in pollutant violation counts from 2011 to 2022, with its first effluent violation enforcement record dating back to 2016. Similarly, Michigan's enforcement activities predominantly pertain to 2017 violations. Therefore, we can make more reliable interpretations of the estimated causal effect for states with more than 15% enforcement percentage.

Montana and Maryland exhibit greater efficacy in regulating effluent violations, as evidenced by their estimates of −2.57 and −3.563, respectively, suggesting that their prompt and effective intervention has successfully moderated the violation trends. Indiana and Texas, known as hotpots for pollution violations, are in need of more focused policies to improve wastewater quality. These findings highlight the dynamic nature of effluent violations over the years, with notable shifts in compliance levels and regulatory enforcement.

Another aspect of our findings is the effective collaboration between federal and state agencies in Idaho, as evidenced by the management of effluent discharge (United States Environmental Protection Agency, 2018). On June 5, 2018, the EPA approved Idaho's application to administer and enforce the Idaho Pollutant Discharge Elimination System (IPDES) Program. Before this transfer of authority, the EPA was solely responsible for issuing NPDES permits in Idaho. Following the transfer, our causal effect estimation indicates a continuation of positive trends in managing effluent violations. Implementing more localized wastewater management strategies under the IPDES Program has contributed to an encouraging negative estimate of −1.882, reflecting the program's effectiveness in mitigating effluent violations.

DISCUSSION

Increasing in effluent violation within the U.S. over time

The EPA initially published the general NPDES regulations in 1972, primarily to administer the NPDES permit program (United States Environmental Protection Agency, 2023b). The EPA has continually revised NPDES regulations to address emerging challenges and improve water quality management. For instance, in 2014, the EPA mandated the use of "sufficiently sensitive" test methods for NPDES permit applications and reporting, (United States Environmental Protection Agency, 2014) which could contribute to detecting more violations. The 2008 amendment, which excluded water transfers from NPDES permitting (United States Environmental Protection Agency, 2008), refocused oversight on direct discharges, influencing violation reporting and possibly contributing to the observed decrease in violations (refer to Figure 4). The substantial rise in violations from 1983 to 2008 can largely be attributed to increased data availability and intensified regulatory scrutiny. However, the fluctuating trends and eventual increase in violations post-2008 suggest evolving compliance challenges within the dynamic landscape of regulatory practices and environmental pressures.

In our analysis of effluent violation trends, we categorize five prevalent pollutants: (1) nitrogen, (2) solids, (3) pathogens, (4) metals, and (5) phosphorus. Nutrient pollution, primarily from excess nitrogen and phosphorus, is identified as one of The U.S.'s most challenging environmental issues, contributing to excessive algae growth that deteriorates water quality, depletes oxygen levels, and disrupts aquatic ecosystems (Schmale et al., 2019;

United States Environmental Protection Agency, 2023f). The escalation in solids-related violations can be attributed to land disturbances like construction and deforestation, stormwater runoff, and industrial activities, which increase suspended solids in water bodies, reducing light penetration and harming aquatic life. These solids can also carry additional pollutants, including heavy metals and pathogens (United States Environmental Protection Agency, 1999b). The observed increase in pathogen-related violations, such as coliform and E. coli, is likely linked to aging sewage infrastructure, combined sewer overflows, and climate change impacts, particularly in urban settings (United States Environmental Protection Agency, 1999a). Meanwhile, the rise in metal-related violations since 2014 may reflect intensified industrial activities, mining operations, and urban runoff, leading to higher concentrations of metals in effluent discharges (Jaishankar et al., 2014). These trends suggest the need for enhanced regulatory oversight, improved wastewater treatment technologies, and targeted pollution control strategies to address the complex challenges of effluent management.

Geographic locations of violations

Our hot-spot analysis, depicted in Figure 6, reveals significant regional disparities in effluent violations across the United States, especially in the eastern North Central region and its overlap with the Ohio watershed and other states in the Rust Belt. Similarly, the western South Central region, encompassing the Lower Mississippi and Texas-Gulf watersheds, shows high violation scores in states like Louisiana and Texas. These clusters of outstanding violations can be attributed to a multifaceted interplay of factors such as industrial and agricultural practices, water system management, population density, urbanization, and regulatory and compliance factors.

Industrial agriculture significantly contributes to water pollution in the United States due to high levels of nutrients like phosphorus and nitrogen from synthetic fertilizers and animal waste. Furthermore, regions characterized by dense industrial activities, especially those involving heavy manufacturing, chemical processing, or mining, are more prone to effluent violations due to the discharge of various pollutants into aquatic ecosystems. Population density and urbanization also play a crucial role. Areas with high population density or those undergoing rapid urbanization face greater challenges in managing wastewater and stormwater effectively, consequently increasing effluent violations.

As discussed in the causal model results section, there are disparities in enforcing environmental regulations and the effectiveness of compliance monitoring across different regions. Such variations in regulatory practices contribute to the regional inconsistencies in effluent violation reporting and aftercare, thereby highlighting the need for a more uniform and stringent approach to environmental regulation and compliance. Understanding these regional differences is critical for effective water resource management. Our analysis shows that areas with intense industrial activity or extensive agricultural lands require specific attention and strategies. This knowledge is indispensable for resource managers and policymakers striving to enhance water quality and ecological health in varied geographic contexts.

Implications for policy improvement

Analysis of NPDES data reveals that not every violation necessitated enforcement actions by regulatory agencies, with significant disparities observed across states. For instance, in Montana, 77.0% (10,731/13,936) of DMR effluent violations triggered enforcement actions, whereas, in Ohio, a mere 4.3% (8170/190,297) led to such actions. This variation may stem from state-specific environmental policies, resource allocation, enforcement priorities, and the particularities of the violations. The CWA decentralized structure delegates primary enforcement responsibility to states, territories, and tribes, as authorized by the EPA (United States Environmental Protection Agency, 2010). This guideline leads to diverse enforcement actions, reflecting each state or territory's distinct policy landscapes and capacities. The EPA intervenes when these entities are unable to enforce regulations. Despite these mechanisms, the prevalence of violations and the inconsistency in enforcement underscore the need for more effective strategies to address water quality issues and control pollution sources.

To enhance compliance within the NPDES framework, we suggest a focused strategy involving targeting facilities with poor performance in pollutant discharge treatment, as identified by trend scores derived from the proposed five metrics. Historically, water enforcement has concentrated on significant individual sources like factories and sewage treatment plants. However, a more strategic approach is necessary with the NPDES program's expansion to nearly 1 million diverse sources, including animal feeding operations and stormwater runoff (United States Environmental Protection Agency, Office of Enforcement and Compliance Assurance OECA, 2010). This approach should leverage data-driven methods to identify facilities posing substantial water quality threats promptly. The proposed trend score system, incorporating multidimensional metrics (violation frequency, severity, temporal trend, recurrence interval, duration, and magnitude), provides a holistic assessment of each facility's compliance status. Individually, each metric offers a unique perspective on facility performance. Furthermore, their integration allows for a comprehensive evaluation, enabling more nuanced and effective regulatory interventions.

Our causal model analysis reveals notable disparities in state compliance and enforcement efficacy concerning pollutant discharge elimination. Despite robust programs in many states, enforcement dynamics should be more consistent. States with positive causal estimates show unimproved violation trends despite frequent enforcement actions. The EPA, tasked with ensuring the CWA's universal enforcement, is recommended to address these irregularities. Inconsistent enforcement creates an uneven playing field for compliant businesses and fails to protect citizens equally. Despite varying political and resource challenges faced by states, the EPA's role in guaranteeing consistent application of the law is imperative. This includes setting clear benchmarks for acceptable state programs and holding both states and the EPA accountable for upholding these standards. In cases where state actions fall short, the EPA should assertively safeguard water quality by disapproving non-protective permits and pursuing federal enforcement against serious violators.

While extensive in its analysis of enforcement actions related to violations, this study acknowledges certain limitations. Primarily, our focus was solely on enforcement actions directly related to effluent violations. This scope overlooks other critical regulatory activities, such as inspections, which also play a significant role in effluent discharge regulation. In addition, the analysis is conducted at a national level, without delving into pollutant-specific investigations. This broader approach may mask dynamics specific to certain pollutants. Future research could benefit from a more detailed examination of various enforcement activities, including routine inspections and their impact on compliance. Moreover, a pollutant-specific analysis could offer deeper insights, enabling more targeted and effective environmental policy recommendations. Such studies would contribute to a more comprehensive understanding of the factors influencing effluent discharge compliance and the efficacy of different regulatory strategies.

Despite some limitations, this paper highlights the essential links between artificial intelligence (AI) and legal frameworks in managing water pollution in the United States. By analyzing effluent violations at the facility level within various states, we reveal ongoing challenges and disparities in technology access, training, and policy implementation that hinder effective water management. This research supports our thematic goal of addressing the knowledge and digital divides and underscores the need for equitable access to resources that turn information into actionable knowledge. Our findings stress the importance of using AI to improve decision-making and ensuring policies are explainable, fair, and ethical.

ACKNOWLEDGMENTS

The authors would like to thank Virginia Tech's A3 Research Lab members (https://ai.bse.vt.edu/) for their inputs and insights, and the Commonwealth Cyber Initiative (CCI) for the support. The authors also acknowledge the use of ChatGPT 3.5 (https://chat.openai.com/) for grammatical checks at the final stage of writing. The views expressed in this paper are solely those of the authors and should not be interpreted as reflecting the views of one of the author's employer; that is, the U.S. Food and Drug Administration. The authors would like to gratefully acknowledge the financial support provided by Deloitte for this research.

CONFLICT OF INTEREST STATEMENT

The authors declare no conflict of interest.

DATA AVAILABILITY STATEMENT

All data used for this study are publicly available via the EPA's NPDES (United States Environmental Protection Agency, 2022).

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ENDNOTES

[1] https://echo.epa.gov/trends/loading-tool/resources#pollutant.

[2] https://www.epa.gov/eg/toxic-and-priority-pollutants-under-clean-water-act.

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How to cite this article: Wang, Y., Sobien, D., Kulkarni, A., & Batarseh, F. A. (2024). Quantifying water effluent violations and enforcement impacts using causal AI. *Policy & Internet*, *16*, 317–338. https://doi.org/10.1002/poi3.402